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A robust network DEA model for sustainability assessment: An application to Chinese Provinces

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Abstract: This paper constructs an Environmental Sustainability index in order to investigate regional efficiency in China between 2000 and 2012. The Environmental Sustainability index consists of a Production Efficiency index and an Eco-efficiency index. A multiplicative relational network data envelopment analysis model is applied, and a window analysis is conducted to capture the efficiency trends over time. The results reveal significant heterogeneity among Chinese provinces for the Environmental Sustainability and the Eco-efficiency indices, while there is a high level of Production Efficiency across all provinces. Furthermore, there are large differences among geographical areas. Specifically, high Production Efficiency levels are reported for the eastern area, whereas, high Eco-efficiency levels are reported for the western area. The reported results provide valuable insights to decision makers, revealing a high potential for improvement in the overall Environmental Sustainability score, especially for the eastern and middle areas. In addition, regional heterogeneity should be taken into account when considering new legislation.

Keywords: Chinese provinces; Eco-efficiency; Environmental Sustainability; Network Data envelopment analysis; Production efficiency.
JEL classification: C61; C67; P25; P28

1. Introduction

The greenhouse effect is one of the major environmental challenges faced by countries in modern society. At the centre of public dialogue is international cooperation, which is vital in order to tackle this challenge. Starting with the Kyoto Protocol, countries cooperate under the United Nations Framework Convention on Climate Change (UNFCCC). The newly sealed Paris Agreement aims at reducing the carbon emissions and the average temperature, which meanwhile has been risen by 2 degrees Celsius above the pre-industrial levels.

As one of the largest countries in the world, the reduction of carbon emission in China has a prominent role on the global environmental agenda. In 2016, total carbon dioxide emissions of China accounted for the 29% of the global emissions (Olivier et al., 2017). In line with the sustainable development principals, China has already promised to reduce its carbon intensity by 40%-45% by 2020 and 60%-65% by 2030, compared to the 2005 levels. The sustainability of the Chinese economy relies heavily on energy consumption (Wu et al., 2017), which not only leads to soaring energy prices, but also causes air pollution (Chen et al., 2013, 2016). In addition, the dependence of energy consumption on the fossil fuels triggers negative health effects (Tanaka, 2015). Furthermore, economic growth has been slowed down after the global financial crisis, which can also be attributed to the ageing population, the declining rural workforce, and substantial energy and environmental issues. As a result, China is trying to shift its strategy of economic development from the gross domestic product (the "Old Normal Growth") to a holistic economic development, which includes economic, political, cultural, social and environmental development. This new phase of economic development has been described as the "New Normal".

There is a growing interest on the sustainable development across the literature. The concept of sustainability as depicted by Brundtland (1987) is the "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*". Sustainable development drew the attention of the academic literature after the UN World Commission on Environment and Development in 1978. Our study considers the aforementioned issues and contributes to the sustainable development literature by proposing an innovative methodological framework in order to study Chinese regions over time. An Environmental Sustainability Index (ESI) is constructed, using a network data envelopment analysis (DEA) model. The ESI is decomposed into two sub-indices, the Production Efficiency Index (PEI) in the first stage and Eco-Efficiency Index (EEI) in the second stage.

The contribution of this paper is two-fold. As for the methodological contribution, we extend the multiplicative network DEA model of Kao and Hwang (2008) to account for multiple time periods, using window analysis (Charnes et al., 1994). To the best of our knowledge, this is the first time that the multiplicative network DEA model is extended to a window analysis framework. Regarding our empirical contribution, we study the environmental sustainability of Chinese regions during 2000-2012, taking into account both the production efficiency and the eco-efficiency dimensions. This is in line with the "New Normal" strategy for the economic development of China. In addition, we take into account the geographical location, as well as the implementation of environmental regulations for each region.

The remainder of this paper is organized as follows: Section 2 presents the literature review, and Section 3 demonstrates the methodology. Section 4 describes the data and discusses the empirical analysis for the Chinese provinces and Section 5 provides our conclusions.

2. Literature Review

The possible synergies between economic and environmental performance have been examined across the literature (Huppes and Ishikawa, 2011; Wang et al., 2018). The concept of sustainable development encompasses both the economic and the environmental aspects. Kuosmanen and Kortelainen (2005) suggested that a significant tool towards sustainability is eco-efficiency, which has the objective to maximize the economic production with the least possible environmental impact. Moreover, Huppes and Ishikawa (2005) describe four different ways eco-efficiency can be defined. In line their definitions, this study adopts the definition of eco-efficiency as the ratio of environmental pressure to production output, which is described as an "*environmental intensity*" index. According to Wusthorn et al. (2011) an environmental intensity index has the attractive feature of decoupling, since it examines the capacity of the economy to grow without hampering the environment. Decoupling is a significant concept towards sustainability (Lu et al., 2015).

DEA is considered an important tool for the assessment of environmental efficiency (Flamos et al., 2004; Peng et al., 2017; Song et al., 2017). The most challenging aspect in defining an environmental DEA model is the modelling of undesirable outputs (Aparicio et al., 2019). According to the traditional axioms by Shephard (1970), (i) inputs are strongly disposable, meaning that the same amount of good and undesirable outputs can be produced using more inputs, (ii) good outputs are strongly disposable, meaning that a lower amount of good outputs can be produced using the same amount of inputs and undesirable outputs. However, the problem arises in the case of undesirable outputs, because assuming strong disposability of undesirable outputs would lead to costless reduction (Førsund, 2009).

Several approaches have been suggested to tackle this issue which can be divided into two groups (Scheel, 2001). The first group applies a data transformation on undesirable outputs and includes them in the model as good outputs, keeping the traditional axioms by Shephard (1970) intact. The undesirable outputs can be transformed by using either the inverse of the output (Lovell et al., 1995) or a translation vector (Seiford and Zhu, 2002, 2005). Imposing strong disposability on the transformed variable does not lead to a costless reduction (Hampf, 2018). The second group modifies the disposability assumptions. The most prominent approach in this group imposes weak disposability on undesirable outputs and assumes the joint production of good and undesirable outputs (Färe and Grosskpof, 2003; Kuosmanen, 2005). Under this approach, undesirable outputs can be decreased only if a simultaneously decrease of the good outputs takes place. Hampf (2018) includes in this group the studies which use undesirable outputs as inputs, an approach which was introduced by Hailu and Veeman (2001).

Our modelling framework is in line with Zaim (2004), who applied a directional distance function approach assuming weak disposability of undesirable outputs, to construct an economic index and an environmental index. The ratio of the two indices can be considered as an environmental intensity index. Different from Zaim (2004), this paper uses a network DEA framework; therefore, it is able to consider both production efficiency and the eco-efficiency dimensions at the same time, and estimate an overall ESI. Since the final outputs in our modelling framework are only undesirable outputs, weak disposability and null-joint production can no longer apply. Therefore, we choose the data translation approach in order to handle undesirable outputs (Seiford and Zhu, 2002, 2005).

As the environmental and energy issue has become an increasing concern for China's economic development and social welfare, the related research on the sustainable efficiency or eco-efficiency is growing rapidly, especially during the recent years (See Table 1). However, the majority of these studies employ the conventional DEA model to analyse the eco-efficiency, without considering possible network structures.

Table 1 about here

3. Methodology

Starting with the pioneer work of Färe and Grosskopf (1996), network data envelopment analysis (DEA) opens the "black box" inside the Decision Making Unit (DMU). Instead of considering only the inputs which enter the system in the beginning of the process and the final outputs at the end of the process, network DEA allows the DMU to consist of two or more stages. The stages can either be connected in series with intermediate variables as links, or operate in parallel. Intermediate variables serve as outputs in one stage and inputs in another stage. Kao and Hwang (2010) classify these models into three categories: independent, connected and relational. This paper uses the relational network DEA approach, which considers the interactions among the stages due to intermediate variables, consequently it is able to calculate stage efficiencies and assumes a mathematical relationship among them.

3.1 The multiplicative efficiency decomposition approach

This section presents the network DEA model of Kao and Hwang (2008) which assumes a multiplicative relationship between the two stages. For the jth DMU $(j = 1, \dots, n)$ we define x_{ij} $(i = 1, \dots, m)$, z_{dj} $(d = 1, \dots, D)$ and y_{rj} $(r = 1, \dots, s)$ as the ith input, the dth intermediate variable and the rth output respectively and v_i, w_d and y_r as their respective multipliers. The overall efficiency for DMU 0 is as follows:

$$E_0 = \frac{\sum_{r=1}^{s} u_r^* y_{r_0}}{\sum_{i=1}^{m} v_i^* x_{i_0}} \leq 1, E_0^1 = \frac{\sum_{d=1}^{D} w_d^* z_{d_0}}{\sum_{i=1}^{m} v_i^* x_{i_0}} \leq 1, E_0^2 = \frac{\sum_{r=1}^{s} u_r^* y_{r_0}}{\sum_{d=1}^{D} w_d^* z_{d_0}} \leq 1 \tag{1}$$

Under the multiplicative efficiency decomposition approach, the overall efficiency can be calculated as the product of the first and second stage efficiencies: $E_0 = E_0^1 \times E_0^2$. It should be noted here that following Kao and Hwang (2008) the multipliers of the intermediate variables are the same for the first and second stage, an assumption which connects the two stages and allows the fractional model to convert into a linear one. It has been argued that the multiplicative network DEA model cannot be extended to the case of variable returns to scale (VRS) (Chen et al., 2009). However, Wang and Chin (2010) demonstrated an approach to extend Kao and Hwang's (2008) model to VRS. Note that u^1 and u^2 are free variables which account for the variable returns to scale.

$$E_0 = max E_0^1 \times E_0^2 = \left[\frac{\sum_{r=1}^{s} \gamma_r y_{r_0} + u^2}{\sum_{i=1}^{m} \omega_i x_{i_0} - u^1}\right] \tag{2}$$

s.t.

$$\frac{\sum_{r=1}^{s} \gamma_r y_{r_j}}{\sum_{i=1}^{m} \omega_i x_{i_j} - u^1} \leq 1,$$

$$\frac{\sum_{r=1}^{s}\gamma_r y_{r_j} + u^2}{\sum_{i=1}^{m}\omega_i x_{i_j}} \le 1,$$

$$\gamma_r, \mu_d, \omega_i \ge 0$$

$$j = 1, \dots, n;\ i = 1, \dots, m; d = 1, \dots, D; r = 1, \dots, s$$

u^1 and u^2 are free in sign

Using the Charnes and Cooper (1965) transformation, model (2) is equivalent to:

$$E_0 = max \sum_{r=1}^{s} \gamma_r y_{r_0} + u^2 \tag{3}$$

s.t.

$$\sum_{i=1}^{m} \omega_i x_{i_0} - u^1 = 1$$

$$\sum_{d=1}^{D} \mu_d z_{d_j} - \sum_{i=1}^{m} \omega_i x_{i_j} + u^1 \le 0,$$

$$\sum_{r=1}^{s} \gamma_r y_{r_j} - \sum_{d=1}^{D} \mu_d z_{d_j} + u^2 \le 0,$$

$$\gamma_r, \mu_d, \omega_i \ge 0$$

$$j = 1, \dots, n;\ i = 1, \dots, m; d = 1, \dots, D; r = 1, \dots, s$$

u^1 and u^2 are free in sign

In case the solution and multipliers in (3) are not unique, an additional linear program is needed in order to calculate the stage efficiencies. Following Kao and Hwang (2008), we decide which of the two stages has a priority and we solve the linear program for that stage first, keeping the overall efficiency at the same level as calculated in (3)[1].

$$E_0^2 = max \sum_{r=1}^{s} \gamma_r y_{r_0} + u^2 \tag{4}$$

s.t.

$$\sum_{d=1}^{D} \mu_d z_{d_0} = 1$$

[1] In this study, priority is given to the efficiency of the second stage because we primarily want to focus on the environmental intensity index and the relationship between economic production and environmental pollution.

$$\sum_{r=1}^{s} \gamma_r y_{r_0} - E_0 \sum_{i=1}^{m} \omega_i x_{i_0} + E_0 \cdot u^1 + u^2 = 0,$$

$$\sum_{d=1}^{D} \mu_d z_{d_j} - \sum_{i=1}^{m} \omega_i x_{i_j} + u^1 \leq 0,$$

$$\sum_{r=1}^{s} \gamma_r y_{r_j} - \sum_{d=1}^{D} \mu_d z_{d_j} + u^2 \leq 0$$

$$\gamma_r, \mu_d, \omega_i \geq 0$$

$$j = 1, \dots, n;\ i = 1, \dots, m; d = 1, \dots, D; r = 1, \dots, s$$

u^1 and u^2 are free in sign

We can calculate the efficiency of the first stage using the optimal solutions from (3) and (4):

$$E_0^1 = \frac{E_0}{E_0^2} \tag{5}$$

3.2 Window analysis of the multiplicative efficiency decomposition approach

DEA window analysis, which originates at the seminal work of Charnes and Cooper (1984), is able to handle data which varies over time and is based on moving averages. Specifically, this approach evaluates the efficiency of a DMU against the efficiency of other DMUs in the same and other periods and also against its own performance over other periods. According to Asmild et al. (2004), window-based DEA analysis captures the efficiency trends over time. Alternative models for the performance analysis over time, such as the global meta-frontier model (Kao and Liu, 2014) which is widely used for the eco-efficiency analysis (Zhang and Chen 2017), treat an additional time period differently. While the addition of a new time period in window analysis will not have an effect on previous performance changes, in the global-meta frontier model the re-estimation of all performance changes will be required, including for previous periods (Pastor et al. 2011).

The first step for the window analysis is to define the size of the rolling window, which is the number of years to be considered every time we run the model. In order to increase the credibility of our results, we choose a narrow three-years window (Asmild et al., 2004). Specifically, we consider *n* DMUs $(j = 1, \dots, n)$ for Ψ periods $(\psi = 1, \dots, \Psi)$ where $x_\psi^j = (x_{1\psi}^j, x_{2\psi}^j, \dots, x_{m\psi}^j)'$, $z_\psi^j = (z_{1\psi}^j, z_{2\psi}^j, \dots, z_{D\psi}^j)'$ and $y_\psi^j = (y_{1\psi}^j, y_{2\psi}^j, \dots, y_{s\psi}^j)'$ describe the input $(i = 1, \dots, m)$, the intermediate variable $(d = 1, \dots, D)$ and the output vector $(r = 1, \dots, s)$ of the *j*th DMU at time ψ.

Furthermore, w_q with $n \times q$ observations define the window which starts at time w, $1 \leq w \leq \Psi$ and has a width of q, $1 \leq q \leq \Psi - w$. Then, matrix of inputs can be defined as:

$$X_{w_q} = (x_w^1, \dots, x_w^n, x_{w+1}^1, \dots, x_{w+1}^n, \dots, x_{w+q}^1, \dots, x_{w+q}^n)$$

the matrix of intermediate variables can be defined as:

$$Z_{w_q} = (z_w^1, \dots, z_w^n, z_{w+1}^1, \dots, z_{w+1}^n, \dots, z_{w+q}^1, \dots, z_{w+q}^n)$$

and the matrix of outputs can be defined as:

$$Y_{w_q} = (y_w^1, \dots, y_w^n, y_{w+1}^1, \dots, y_{w+1}^n, \dots, y_{w+q}^1, \dots, y_{w+q}^n)$$

The VRS version of the multiplicative network DEA model can be represented as follows:

$$E_{w_q\psi} = \max \gamma \cdot y'_\psi + U^2 \tag{6}$$

s.t.

$$\omega \cdot x'_\psi - U^1 = 1$$

$$M \cdot Z_{w_q} - \Omega \cdot X_{w_q} + U^1 \leq 0$$

$$\Gamma \cdot Y_{w_q} - M \cdot Z_{w_q} + U^2 \leq 0$$

$$\gamma_r, \mu_d, \omega_i \geq 0$$

$$j = 1, \dots, n \times q;\ i = 1, \dots, m; d = 1, \dots, D; r = 1, \dots, s$$

Accordingly, the efficiency of the second stage is:

$$E_{w_q\psi}^2 = \max \gamma \cdot y'_\psi + U^2 \tag{7}$$

s.t.

$$\mu \cdot z'_\psi = 1$$

$$\gamma \cdot Y_{w_q} - E_{w_q} \cdot \Omega \cdot X_{w_q} + E_{w_q} \cdot U^1 + U^2 = 0$$

$$M \cdot Z_{w_q} - \Omega \cdot X_{w_q} + U^1 \leq 0$$

$$\Gamma \cdot Y_{w_q} - M \cdot Z_{w_q} + U^2 \leq 0$$

$$\gamma_r, \mu_d, \omega_i \geq 0$$

$$j = 1, \dots, n \times q;\ i = 1, \dots, m; d = 1, \dots, D; r = 1, \dots, s$$

Finally, the efficiency of the first stage using the optimal solutions from (6) and (7) is:

$$E_{w_q\psi}^1 = \frac{E_{w_q\psi}}{E_{w_q\psi}^2} \tag{8}$$

4. Empirical Analysis

4.1 Variable and model description

Our empirical application investigates the sustainability efficiency of the 30 Chinese provinces (or autonomous regions, municipalities)[2] for the time period 2000-2012 based on the data availability. As most of the relevant data is missing, Tibet is dropped from the sample. Considering the particularity of Hong Kong, Macau and Taiwan, they are also excluded from the sample. The data is collected from the China Statistical Yearbook (National Bureau of Statistics of China, 2013a), China Environment Statistical Yearbook (National Bureau of Statistics of China, 2014) and China Energy Statistical Yearbook (National Bureau of Statistics of China, 2013b), dating from 2001 to 2013.

The first stage of the decomposed sustainability efficiency measures the production efficiency, whereas, the second stage measures the eco-efficiency. Following Huppes and Ishikawa (2005), eco-efficiency can be defined as environmental intensity and calculated as the ratio of the undesirable output which is the environmental pollutant to desirable output which is the economic production. The production process of each province consumes capital, labour and energy as inputs and produces GDP which is the intermediate variable. The eco-efficiency process uses GDP as input and produces CO_2 and SO_2 which are the final outputs. Note that the final outputs of the DMU are undesirable, meaning that a higher value of CO_2 and SO_2 should lead to a lower efficiency score. In order to accommodate for undesirable outputs, Seiford and Zhu's (2002) transformation is applied following formula:

$$f(\mathrm{U}) = -\mathrm{U} + \beta. \tag{9}$$

In equation (9), U represents the vector of the undesirable outputs, which is multiplied by -1. In addition, β represents a proper translation vector such that $f(U) > 0$. Note that weak disposability is usually assumed for the environmental problems, since the reduction of an environmental pressure such as CO_2, requires the reduction of the economic production (Färe and Grosskopf 2004). However, since the final outputs in our modelling framework are only undesirable outputs, weak disposability and null-joint production can no longer apply. Therefore, we choose the data translation approach in order to handle undesirable outputs (Seiford and Zhu, 2002, 2005).

The general framework of our overall two-stage ESI is straightforward. Specifically, a high value of ESI means that the economy is able to expand (in the first stage) without hampering the

[2] There are four municipalities, including Beijing, Shanghai, Tianjin and Chongqing. Meanwhile, there are five autonomous regions, including Xinjiang, Tibet, Inner Mongolia, Guangxi and Ningxia. They all have the same the administrative status with other provinces.

environment (in the second stage). Therefore, our overall ESI index satisfies the concept of sustainability and serves as a decoupling indicator (Wusthorn et al., 2011).

In order to ensure the validity of the model specification, Avkiran (1999) suggested an isotonicity test, which was adopted by a number of studies across the literature (Mostafa, 2009; Tsolas, 2015; Tsolas and Charles, 2015). This test investigates whether increasing amounts of inputs results in increasing amount of outputs, using the intercorrelations between inputs and outputs. All our variables in the first stage pass this test. Indeed, all the correlations among the three inputs and the one output are positive and significant. There is also one very high correlation coefficient (between capital and GDP). According to Charnes et al. (1994), inputs and outputs which are highly correlated do not have a significant effect on the DEA efficiency score, however, there is discrimination power is lower (Siriopoulos and Tziogkidis 2010). Regarding the second stage, the outputs are anti-isotonic (Dyson et al., 2001; Scheel, 2001) and they were handled using the translation vector (9).

Regarding our modelling framework, we use a VRS model in order to catch any possible scale effects across the Chinese provinces. In order to use models (5)-(7) we need to specify the width of the window. According to Asmild et al. (2004) we choose a narrow 3-year window. Starting with the first window, it includes 2000, 2001 and 2002. Next, the second window excludes 2000 and includes 2003, keeping the width constant at 3 years, and the analysis continues until all the windows are formed. Therefore, there are 11 windows into the analysis and each of them consists of 90 DMUs (n×w= 30×3=90), with a total of 990 DMUs. Descriptive statistics are presented at Table 2 and Figure 1 presents the visual illustration of the proposed model.

Table 2 about here

Figure 1 about here

DEA models are deterministic in nature, which means that they do not allow any random noise and every deviation from the frontier is due to inefficiency. This results to a drawback of DEA models, which is the sensitivity to extreme values and outliers. Such extreme observations can impact the shape of the efficient frontier, while their isolated location casts doubt on the credibility of the data (Thanassoulis et al., 2011). The use of DEA window analysis greatly increases the number of observations, which leads to more robust results.

4.2 Empirical Results and discussion

An illustrative example of the window analysis for the Guangdong Province, which is the biggest Chinese province in terms of population[3], is provided at Table 3. The first part of Table 3 presents the overall ESI, the second part presents the PEI and the last part presents EEI. Our findings can be analysed either by investigating the Table's rows or by investigating the Table's columns. On the one hand, rows indicate the trend and the behaviour across the same window. On the other hand, columns demonstrate the efficiency of a specific year and its stability across different windows. We can observe that the scores of the ESI and the EEI are relative stable across the years, with a slight increase 3% over the entire period. On the same time, Guangdong Province achieves perfect score for the PEI across the entire period, which is consistent with the results of other scholars (Wang et al., 2013b). The high PEI can perhaps be explained by the intensive competition in the province, mainly due to multinational companies. In addition, Guangdong Province is the first pilot-reform area of "Open-up and reform" since 1978. The local economy has been booming with the international and FDI flowing into China. Plenty of private companies have been set up in the last decades. Moreover, the GDP of Guangdong Province has been ranked as the top one among all the China's provinces for about thirty years. Note that the last line of each part of Table 3 calculates the average results for each year.

Table 3 about here

Table 4 presents the average results for each year for all Chinese provinces. The average results for the overall ESI reveal some heterogeneity among the Chinese provinces. All but three provinces range from 0.611 (Shanghai) to 0.779 (Gansu). Qinghai is the best performing province with an average efficiency of 0.999, closely followed by Hunan (0.971) and Ningxia Hui (0.946). Furthermore, the results are stable across the time period. The largest increase in terms of average annual growth was achieved by Beijing (0.55%) and the largest decrease by Inner Mongolia (0.69%). Figure 2 demonstrates the visual representation of the results[4].

[3] Similar tables have been created for all Chinese provinces and are available upon request. Here we present only one due to space restrictions.
[4] Bright green colour depicts the most efficient countries and red colour depicts the least efficient countries. The range among each class is 0.10 for all classes. Starting from the better classes in terms of efficiency scores they are classified as bright green, dark green, blue, light blue, turquoise, yellow, rose, pink, orange and red.

Table 4 about here

Figure 2 here

The average PEI scores are very high for all provinces across all years. Specifically, the scores range from 0.935 for Guizhou to perfect unity for Guangdong, Tianjin and Qinghai. The results are stable across time since the largest increase was only 0.20% (Jiangsu) and the largest decrease 0.47% (Guangxi Zhuang). Meanwhile, most of the provinces experienced a slight decrease of production efficiency, which is probably due to the global financial crisis. The average EEI scores are quite similar with the overall ESI scores. All but five provinces range from 0.614 (Guangdong) to 0.788 (Xinjiang). Qinghai is the best performing province with an average efficiency of 0.999, closely followed by Ningxia province (0.974) and Hunan province (0.973). In addition, two provinces achieved efficiency over 80% (Gansu 0.812 and Guizhou 0.814). The results are stable across the entire time period, showing a slightly growing trend for the majority of sample provinces. The largest increase in terms of average annual growth was achieved by Beijing (0.54%) and the largest decrease by Inner Mongolia (0.29%). As the overall ESI is mainly driven by the EEI, it is quite important to focus on the improvement of the latter one. The most developed provinces, like Beijing, Shanghai, Zhejiang, Shandong and Guangdong, all have displayed higher growth rate during the sample period.

Referring to the literature, the 30 provinces are classified into different groups, in order to address the regional heterogeneity. First, they are divided into three groups, i.e. eastern, middle and western areas[5], based on their location. According to Figure 3, the eastern area has the highest PEI, while the western region achieves best performance on the EEI. The China's eastern region experienced the most remarkable economic development during the last forty years, contributing 55.34% to the total GDP in 2014. The overall ESI is driven by the EEI, since they follow similar patterns. In addition, eastern and middle areas perform similarly, especially after 2005. Both of them have great potential to improve in terms of the overall ESI (by 30%). Meanwhile, the west region can improve its ESI by about 20% in order to reach the efficient frontier.

[5] The eastern area includes the eight coastal provinces, Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong and Hainan, and the three municipalities of Beijing, Tianjin and Shanghai. The middle area consists of 10 inland provinces, Heilongjiang, Jilin, Inner Mongolia, Henan, Shanxi, Anhui, Hubei, Hunan, Jiangxi and Guangxi, it is the agricultural base for the country. The western area contains 1 municipality and 9 provinces, Chongqing and provinces of Gansu, Guizhou, Ningxia, Qinghai, Shaanxi, Tibet, Yunnan, Xinjiang and Sichuan.

Furthermore, Figure 3 shows the dynamics of the three indicators during the sample period. In contrast to the EEI, which has an upward trend, the PEI decreased at the beginning of the sample period. Specifically, there was a sharp decrease on the PEI in the middle area starting in 2005. Owing to positive and negative effects being neutralized, the overall ESI displayed a stable pattern before 2009. After this point, the decrease rate of PEI exceeded the increase rate of EEI, leading to the decline of the overall ESI.

Figure 3 about here

The kernel density plots for overall ESI, PEI and EEI are shown in Figure 4. There are obvious differences in distribution patterns among the three areas, indicating regional heterogeneity. In addition, results in certain areas follow the bimodal distribution, suggesting that there is divergence in the specific groups. Meanwhile, the location does not imply a prior advantage on the performance of PEI, which contradicts the findings of previous studies (Wang et al., 2013a,b; Huang et al., 2014).

Figure 4 about here

Furthermore, the 30 provinces are further classified into two groups, based on the regulations on the SO_2 emission[6]. There are 13 regulated provinces in the list of government. We first check whether there are any significant differences in the three indicators between the two groups, using the Wilcoxon-Mann-Whitney rank-sum test. As shown in Table 5, all of the null hypotheses are rejected at the 10% significance level, which implies that the three indices behaved differently in the presence of government's regulation regarding the SO_2 emissions.

Table 5 about here

[6] According to the Air Pollution Prevention and Control Law, the government decided to restrict the SO_2 emissions in some provinces since 1998, including Beijing, Tianjin, Hebei, Jilin, Liaoning, Inner Mongolia, Shandong, Jiangsu, Henan, Shaanxi, Gansu, Ningxia and Xinjiang. As the regulation on carbon emission has not launched until the beginning of 21 century.

We further display the kernel density plots for the ESI in Figure 5, which indicates obvious differences in distribution patterns for the two groups. This further validates the results presented above.

Figure 5 about here

Figure 6 presents the box plot of unregulated and regulated area for comparison. It appears that the regulated area has higher overall ESI and EEI in comparison to the unregulated area. Meanwhile, the regulated area's PEI seems slightly lower than its counterparty. Overall, the regulation on the SO2 emissions improved the ESI of the Chinese provinces, despite a slightly decrease in PEI.

Figure 6 about here

The ESI trend for the two distinct groups is shown in Figure 7. The EEI has an increasing trend for both areas. Specifically, regulated area has a leading role in the EEI ever since 2000, which further justifies the effect of regulatory policy. With respect to the PEI, the regulated area displayed an insignificant disadvantage over the unregulated one. After 2005, the gap between the two has been increasing, which may have been caused by the regulatory constraints. Hence, the overall ESI has been worsened for the regulated area since 2005, due to the PEI.

Figure 7 about here

5. Conclusions and Policy implications

As environmental and sustainable development issues have attracted increasing attention in China, the related research on sustainable efficiency and eco-efficiency is growing rapidly. Our study contributes to the sustainable development literature by proposing an innovative methodological framework to study Chinese regions over time. Specifically, this paper analyses the sustainability efficiency of the Chinese provinces during the period of 2000-2012, following a window-based multiplicative network DEA approach. An ESI is constructed, using a network DEA model. The ESI is decomposed into two sub-indices, PEI in the first stage and EEI in the second stage. Different from previous studies, the network structure of the sustainability index takes into account both the production efficiency and the eco-efficiency dimensions. This is in line with the sustainability principals in general, and the “New Normal” strategy for the economic development of China in particular.

Results show that the ESI of Chinese provinces has been significantly improved during the examined time period. Furthermore, the overall ESI reveals heterogeneity among the provinces. This is consistent with previous studies which found that the performance of Chinese regions is not uniform both in production and in environmental terms (Wang et al., 2013a,b; Huang et al., 2014). The mean score for the ESI is 0.723, which reveals a great potential for improvement. The PEI scores are quite high for all provinces across the entire time period under investigation, with an average score of 0.976. Meanwhile, the EEI scores are quite similar with the overall ESI scores, with a mean of 0.740.

We further divide the provinces into different groups according to their geographical location as well as the environmental regulations. In the first case, the 30 provinces are divided into three areas, i.e. the eastern, middle and western. There is heterogeneity regarding the geographical location for the EEI and as a result the overall ESI. However, the results indicate that the location does not imply a prior advantage on the performance of PEI, which contradicts the findings of previous studies (Wang et al., 2013a,b; Huang et al., 2014). The eastern area experienced the highest results in PEI, while the western area had the best performance in EEI. The eastern and middle areas had a similar performance in ESI, especially after 2005. Both of them have great potential to improve the overall efficiency up to 30%. Meanwhile, the west area can enhance its performance up to 20%. Furthermore, we classify the provinces into two groups based on the regulations for the SO_2 emissions. The regulated area has a leading role in the EEI ever since 2000. However, the regulated area displays worse PEI than the unregulated one, especially after 2005 when the Chinese economic growth accelerated and the gap between the two has been increased. Due to the negative effect of regulation, the overall ESI has been worsened for the regulated area since 2005.

There is large space for China to enhance its ESI, especially for the eastern and middle areas. When initiating reforms or regulations, the government should pay attention to the regional heterogeneity. Specifically, the government should aim to enact different sets of policies in east, central and west areas, in order to improve the environmental sustainability (Choi and Lee 2009). Therefore, each area should be considered as a separate case and based on its own characteristics, such as the level of economic growth, the social environment and the environmental needs (Yu and Choi, 2015). For the provinces located at the eastern and middle areas, their ESI is restricted by the EEI. Although some of the developed provinces has already made progress on the EEI, they still need to accelerate the green economic growth, which aims for social equity and well-being, with diminishing environmental threats (Chao et al., 2012). Furthermore, the central government can take actions in order to transfer capital towards the deficit areas, aiming to improve environmentally friendly technologies and R&D (Yu and Choi, 2015). In addition, when launching emission regulations, the development of new industries should be encouraged, in order to offset the negative effects of restrictions on old industries.

Further research is still needed on this area. The proposed framework is in line with the sustainability principals; therefore, it can be used to measure the performance of other countries, taking into account the production and the environmental dimensions. Furthermore, due to the availability of the carbon emission data, this paper has not focused on the environmental regulation during recent years. In addition, other environmental pollutants, such as the PM 2.5 and waste water, can also be considered into a future analysis.

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Table 1: Literature on the eco-efficiency of different provinces in China

Author	Methodology	Inputs and outputs	Time Period	Sample
Zhang et al. (2008)	DEA-CCR	Input: Water resource, Raw mining resource, Energy Output: Value-added of industry, COD, NO_X, SO_2, Soot emission, Dust emission, Industrial solid wastes	2005	30 provinces
Li and Hu (2012)	SBM	Input: Capital, Labor, Energy Output: GDP, CO_2, SO_2	2005-2009	30 provinces
Wang et al. (2013a)	RAM-DEA	Input: Capital, Labor, Energy Output: GDP, CO_2	2006-2010	30 provinces
Wang et al. (2013b)	MEA	Input: Capital, Labor, Energy Output: GDP, CO_2	1997-2010	30 provinces
Wang et al. (2013c)	non-radial DEA, DEA window analysis	Input: Capital, Labor, Energy Output: GDP, CO_2, SO_2	2000-2008	29 provinces
Huang et al. (2014)	GB-US-SBM model	Input: Capital, Land, Labor and Energy Output: GDP, environment index	2000-2010	30 provinces
Yang et al. (2015)	Supper-efficiency DEA	Input: Capital, Labor, Energy Output: GDP, CO_2, SO_2	2000-2010	30 provinces
Chu et al. (2016)	Two-stage Network DEA	Input: capital, Labor, Energy, Pollution control investments Intermediate: Waste Water, Waste gas, Solid Waste Output: GDP, Waste Water removed, Waste gas removed, Solid waste removed	2013	30 provinces
Zhang et al. (2016)	SBM	Input: Capital, Labor, Energy Output: GDP, COD, CO_2, SO_2	2005-2011	30 provinces

Ren et al. (2016)	DEA-DDF	Input: Energy, Labor, Land, Water Output: GDP, Industrial waste water, Chemical oxygen, SO_2, Soot emission, Dust emission, solid waste	2000-2013	30 provinces
Yang and Zhang (2018)	Global DEA, Malmquist-Luenberger index	Input: Capital stock, Labor, Construction land area, Water, Energy Output: GDP, Solid Waste emission, Waste Water, SO2, Household Refuse, Soot and Dust emission	2003-2014	30 provinces

Table 2: Descriptive statistics

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Capital	**mean**	7860.26	8802.88	9893.48	11256.01	12887.48	14906.78	17323.12	20148.95	23402.12	27421.90	32096.07	37311.49	43098.65
	Stdev	5059.46	5739.78	6517.13	7513.96	8687.58	10132.74	11768.52	13565.96	15517.59	17988.43	20775.13	23972.29	27035.02
	Min	1195.31	1368.19	1571.08	1808.51	2059.04	2338.17	2644.85	2987.68	3362.38	3882.35	4562.18	5392.49	6535.35
	Max	19945.72	22523.83	25474.13	29530.21	34005.36	39679.18	46059.69	53000.56	60804.50	71330.97	83356.20	96223.94	110064.98
Labor	**mean**	2095.18	2097.60	2121.69	2157.74	2205.81	2262.90	2318.09	2373.24	2426.36	2493.07	2555.31	2641.09	2663.03
	Stdev	1422.84	1419.69	1414.27	1432.98	1458.68	1509.50	1547.77	1587.67	1620.22	1662.03	1700.90	1710.59	1711.99
	Min	238.57	240.32	247.30	254.26	263.08	267.62	271.80	276.29	276.79	285.54	294.10	309.18	310.89
	Max	5571.67	5516.59	5522.00	5535.68	5587.45	5662.41	5717.70	5772.72	5835.45	5948.78	6041.56	6198.00	6288.00
Energy	**mean**	4949.40	5244.19	5649.67	6415.15	7432.88	8845.80	9718.07	10517.76	11038.67	11719.66	12674.83	14023.04	14328.53
	Stdev	3060.11	3255.10	3503.03	3975.43	4668.28	6120.00	6729.56	7228.63	7527.94	7774.99	8354.37	9157.12	9266.10
	Min	424.08	466.48	545.12	623.76	657.61	699.73	861.87	1001.01	1205.23	1288.69	1253.58	1381.52	1615.75
	Max	11970.47	12321.39	12194.96	14272.37	18052.62	26333.26	29442.20	32085.32	33423.48	34124.86	36987.29	38973.31	40630.76
GDP	**mean**	3279.58	3596.01	3987.21	4478.03	5089.77	5760.36	6556.44	7509.58	8402.18	9380.27	10610.43	11856.83	13069.41
	Stdev	2538.82	2799.32	3134.72	3578.10	4111.92	4702.23	5401.02	6195.51	6880.55	7612.50	8541.62	9397.35	10212.01
	min	263.68	294.56	330.14	369.30	414.62	465.21	521.96	587.21	661.78	728.62	840.10	953.51	1070.34

	max	10741.25	11867.83	13336.29	15316.33	17581.26	20064.83	23035.81	26460.15	29221.18	32041.04	36030.23	39628.60	42860.33
CO_2	**mean**	12934.88	13707.07	14809.62	16853.00	19590.54	23225.24	25527.02	27570.14	28998.25	30761.25	33300.06	36922.20	37684.20
	stdev	7903.79	8438.36	9185.73	10457.86	12311.16	16078.51	17723.15	19036.53	19949.57	20578.63	22145.10	24379.07	24617.79
	min	977.35	1066.24	1269.62	1472.99	1744.88	1872.27	2339.28	2560.55	2892.14	3262.02	3308.75	3629.54	4260.97
	max	30773.91	31367.55	32667.70	38048.88	47760.00	69261.08	77351.87	84115.31	88226.56	90102.81	97449.01	102411.23	10667.02
SO_2	**mean**	64.84	62.57	62.60	71.96	75.17	84.78	86.21	82.26	77.36	73.81	72.29	73.82	70.47
	stdev	43.80	43.37	42.50	46.46	46.53	50.94	51.03	47.79	44.41	42.07	40.88	44.35	41.93
	min	2.00	2.00	2.20	2.30	2.30	2.20	2.40	2.56	2.20	2.20	2.88	3.26	3.41
	max	180.00	172.00	169.00	184.00	182.00	200.00	196.00	182.00	169.00	159.00	154.00	183.00	175.00

Table 3: A three-year window analysis for the Guangdong Province

Overall efficiency	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
W1	0.601	0.594	0.587										
W2		0.606	0.599	0.590									
W3			0.611	0.602	0.593								
W4				0.613	0.605	0.597							
W5					0.617	0.608	0.600						
W6						0.620	0.611	0.603					
W7							0.623	0.614	0.609				
W8								0.626	0.620	0.615			
W9									0.632	0.626	0.619		
W10										0.635	0.628	0.623	
W11											0.642	0.636	0.631
Average	**0.601**	**0.600**	**0.599**	**0.602**	**0.605**	**0.608**	**0.611**	**0.615**	**0.620**	**0.625**	**0.630**	**0.629**	**0.631**
Production efficiency													
W1	1.000	0.999	1.000										
W2		1.000	1.000	1.000									
W3			1.000	1.000	1.000								
W4				1.000	1.000	1.000							
W5					1.000	1.000	1.000						
W6						1.000	1.000	1.000					
W7							1.000	1.000	1.000				
W8								1.000	1.000	1.000			
W9									1.000	1.000	1.000		
W10										1.000	1.000	1.000	
W11											1.000	1.000	1.000
Average	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
Eco-efficiency													

W1	0.601	0.594	0.587										
W2		0.606	0.599	0.590									
W3			0.611	0.602	0.593								
W4				0.613	0.605	0.597							
W5					0.617	0.608	0.600						
W6						0.620	0.612	0.603					
W7							0.623	0.614	0.609				
W8								0.626	0.620	0.615			
W9									0.632	0.626	0.619		
W10										0.635	0.628	0.623	
W11											0.642	0.636	0.631
Average	**0.601**	**0.600**	**0.599**	**0.602**	**0.605**	**0.608**	**0.612**	**0.615**	**0.620**	**0.625**	**0.630**	**0.629**	**0.631**

Table 4: Efficiency scores over time

Province	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Average	Average Annual Growth
Overall Sustainability efficiency index															
BJS	0.691	0.689	0.685	0.690	0.698	0.706	0.704	0.705	0.713	0.715	0.721	0.773	0.735	0.710	0.005526
TJS	0.749	0.745	0.741	0.742	0.748	0.754	0.750	0.750	0.748	0.748	0.748	0.757	0.745	0.748	-0.000428
HEB	0.632	0.629	0.627	0.632	0.636	0.639	0.641	0.645	0.647	0.650	0.656	0.652	0.652	0.641	0.002594
SAX	0.730	0.725	0.721	0.724	0.727	0.728	0.726	0.724	0.725	0.725	0.726	0.720	0.717	0.725	-0.001498
IMZ	0.760	0.757	0.752	0.749	0.744	0.736	0.727	0.721	0.718	0.714	0.713	0.705	0.699	0.730	-0.006884
LNS	0.655	0.656	0.656	0.661	0.663	0.666	0.667	0.668	0.667	0.670	0.673	0.669	0.668	0.665	0.001580
JLS	0.733	0.732	0.730	0.736	0.741	0.747	0.737	0.727	0.721	0.719	0.718	0.712	0.709	0.728	-0.002793
HLJ	0.680	0.681	0.682	0.690	0.697	0.707	0.710	0.712	0.716	0.717	0.722	0.716	0.714	0.703	0.004087
SHS	0.657	0.656	0.654	0.658	0.661	0.669	0.671	0.673	0.679	0.685	0.691	0.704	0.699	0.674	0.005181
JSS	0.599	0.603	0.605	0.609	0.609	0.609	0.613	0.617	0.622	0.627	0.632	0.634	0.639	0.617	0.005412
ZJS	0.626	0.623	0.624	0.629	0.628	0.628	0.629	0.631	0.637	0.641	0.646	0.646	0.649	0.634	0.003074
AHS	0.688	0.686	0.685	0.691	0.696	0.706	0.705	0.704	0.705	0.707	0.711	0.706	0.702	0.699	0.001684
FJS	0.677	0.677	0.675	0.679	0.686	0.692	0.691	0.689	0.693	0.693	0.696	0.692	0.692	0.687	0.001774
JXS	0.733	0.730	0.724	0.723	0.729	0.734	0.729	0.728	0.730	0.733	0.734	0.730	0.732	0.730	-0.000112
SHD	0.603	0.599	0.597	0.600	0.602	0.604	0.606	0.611	0.617	0.622	0.626	0.629	0.633	0.611	0.004051
HEN	0.637	0.635	0.633	0.638	0.641	0.642	0.642	0.641	0.640	0.640	0.642	0.638	0.646	0.640	0.001187
HUB	0.657	0.655	0.653	0.659	0.664	0.672	0.672	0.674	0.678	0.680	0.684	0.679	0.677	0.669	0.002541
HUN	0.677	0.674	0.672	0.678	0.682	0.687	0.688	0.688	0.691	0.692	0.694	0.689	0.690	0.685	0.001596
GDS	0.601	0.600	0.599	0.602	0.605	0.608	0.611	0.615	0.620	0.625	0.630	0.629	0.631	0.614	0.004172
GXZ	0.730	0.727	0.724	0.730	0.735	0.740	0.734	0.729	0.728	0.726	0.721	0.710	0.704	0.726	-0.002899
HAN	1.000	0.899	0.931	0.972	0.939	1.000	0.999	1.000	0.998	0.956	0.947	0.994	0.989	0.971	0.000071
CQS	0.741	0.738	0.732	0.741	0.745	0.747	0.744	0.745	0.736	0.740	0.744	0.737	0.738	0.740	-0.000252
SCS	0.658	0.656	0.654	0.657	0.661	0.672	0.673	0.672	0.674	0.676	0.682	0.681	0.680	0.669	0.002745
GZS	0.751	0.747	0.742	0.744	0.751	0.765	0.767	0.768	0.772	0.775	0.780	0.774	0.766	0.762	0.001737
YNS	0.702	0.700	0.699	0.704	0.712	0.719	0.717	0.716	0.721	0.724	0.725	0.717	0.713	0.713	0.001344
SNX	0.696	0.694	0.692	0.697	0.702	0.712	0.708	0.707	0.707	0.709	0.710	0.705	0.701	0.703	0.000710

GSS	0.797	0.792	0.786	0.790	0.801	0.810	0.807	0.805	0.800	0.802	0.805	0.797	0.791	0.799	-0.000696
QHS	1.000	0.994	0.996	1.000	0.998	1.000	1.000	1.000	1.000	0.996	1.000	0.998	1.000	0.999	0.000004
NXZ	0.968	0.961	0.952	0.952	0.957	0.960	0.954	0.950	0.947	0.929	0.934	0.920	0.918	0.946	-0.004376
XJZ	0.728	0.726	0.724	0.728	0.735	0.743	0.740	0.741	0.747	0.753	0.760	0.755	0.750	0.741	0.002510
Production efficiency index															
BJS	0.999	1.000	0.997	0.997	0.998	0.998	0.997	0.997	0.999	0.999	0.999	1.000	1.000	0.998	0.000115
TJS	1.000	0.999	1.000	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000011
HEB	0.966	0.962	0.960	0.960	0.960	0.960	0.959	0.958	0.954	0.951	0.954	0.952	0.949	0.957	-0.001466
SAX	0.985	0.981	0.981	0.983	0.986	0.984	0.977	0.973	0.966	0.955	0.954	0.951	0.947	0.971	-0.003233
IMZ	1.000	1.000	1.000	0.998	0.996	0.992	0.983	0.976	0.973	0.968	0.965	0.960	0.953	0.982	-0.003986
LNS	0.993	0.994	0.996	0.997	0.994	0.992	0.989	0.987	0.980	0.980	0.980	0.978	0.975	0.987	-0.001566
JLS	0.997	0.997	0.995	0.996	0.996	0.993	0.983	0.973	0.964	0.959	0.954	0.951	0.950	0.978	-0.004020
HLJ	0.983	0.985	0.988	0.992	0.996	0.999	1.000	0.999	0.999	0.996	0.997	0.994	0.990	0.994	0.000634
SHS	0.999	0.999	0.998	0.997	0.998	0.996	0.997	1.000	1.000	0.999	1.000	0.999	1.000	0.999	0.000099
JSS	0.973	0.979	0.985	0.985	0.981	0.976	0.977	0.980	0.982	0.983	0.985	0.990	0.996	0.983	0.001984
ZJS	0.979	0.977	0.981	0.985	0.979	0.972	0.970	0.968	0.969	0.967	0.968	0.969	0.970	0.973	-0.000787
AHS	0.984	0.982	0.982	0.982	0.985	0.983	0.982	0.980	0.977	0.977	0.979	0.977	0.973	0.980	-0.000911
FJS	1.000	1.000	0.998	0.998	0.997	0.993	0.995	0.993	0.993	0.989	0.990	0.986	0.987	0.994	-0.001049
JXS	1.000	0.997	0.991	0.986	0.983	0.980	0.976	0.973	0.975	0.976	0.975	0.975	0.978	0.982	-0.001858
SHD	0.977	0.971	0.970	0.968	0.967	0.966	0.966	0.968	0.971	0.972	0.973	0.978	0.983	0.972	0.000545
HEN	0.974	0.972	0.969	0.968	0.969	0.966	0.962	0.956	0.949	0.943	0.940	0.937	0.948	0.958	-0.002264
HUB	0.963	0.960	0.958	0.958	0.959	0.960	0.960	0.960	0.961	0.961	0.963	0.961	0.960	0.961	-0.000284
HUN	0.992	0.990	0.986	0.987	0.987	0.982	0.981	0.980	0.979	0.978	0.977	0.973	0.976	0.982	-0.001408

GDS	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000000
GXZ	1.000	0.996	0.995	0.994	0.990	0.988	0.984	0.978	0.975	0.970	0.961	0.951	0.945	0.979	-0.004740
HAN	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	0.998	0.996	1.000	0.994	0.989	0.998	-0.000920
CQS	0.980	0.978	0.973	0.975	0.970	0.964	0.963	0.965	0.957	0.961	0.967	0.966	0.972	0.969	-0.000711
SCS	0.977	0.975	0.972	0.970	0.971	0.974	0.975	0.974	0.969	0.969	0.975	0.979	0.980	0.974	0.000273
GZS	0.934	0.931	0.927	0.925	0.929	0.934	0.937	0.939	0.939	0.940	0.943	0.943	0.939	0.935	0.000439
YNS	0.957	0.954	0.953	0.952	0.954	0.949	0.947	0.945	0.947	0.947	0.944	0.940	0.937	0.948	-0.001780
SNX	0.936	0.935	0.937	0.938	0.939	0.940	0.938	0.938	0.937	0.937	0.937	0.936	0.934	0.937	-0.000154
GSS	0.995	0.992	0.988	0.987	0.990	0.991	0.990	0.987	0.977	0.975	0.974	0.971	0.967	0.983	-0.002411
QHS	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	0.999	1.000	0.998	1.000	1.000	0.000001
NXZ	0.988	0.987	0.985	0.982	0.977	0.974	0.973	0.971	0.971	0.956	0.961	0.954	0.958	0.972	-0.002516
XJZ	0.943	0.941	0.940	0.940	0.939	0.938	0.935	0.937	0.939	0.940	0.943	0.942	0.939	0.940	-0.000357
Eco-efficiency index															
BJS	0.692	0.689	0.687	0.692	0.699	0.708	0.706	0.707	0.714	0.716	0.721	0.773	0.735	0.711	0.005405
TJS	0.749	0.745	0.741	0.742	0.748	0.754	0.750	0.750	0.748	0.748	0.748	0.757	0.745	0.748	-0.000440
HEB	0.654	0.654	0.654	0.658	0.662	0.665	0.669	0.673	0.678	0.683	0.687	0.686	0.686	0.670	0.004064
SAX	0.741	0.739	0.735	0.736	0.737	0.740	0.743	0.744	0.751	0.759	0.761	0.757	0.757	0.746	0.001752
IMZ	0.760	0.757	0.752	0.750	0.747	0.742	0.740	0.738	0.738	0.737	0.739	0.734	0.733	0.744	-0.002908
LNS	0.660	0.660	0.659	0.663	0.667	0.671	0.675	0.677	0.681	0.684	0.687	0.684	0.685	0.673	0.003152
JLS	0.736	0.734	0.733	0.738	0.744	0.752	0.750	0.748	0.748	0.750	0.753	0.749	0.747	0.745	0.001225
HLJ	0.692	0.691	0.690	0.695	0.700	0.707	0.710	0.712	0.717	0.720	0.724	0.721	0.721	0.708	0.003447
SHS	0.658	0.657	0.655	0.659	0.662	0.671	0.673	0.673	0.679	0.685	0.691	0.704	0.699	0.675	0.005085
JSS	0.616	0.615	0.614	0.618	0.621	0.624	0.627	0.630	0.634	0.637	0.642	0.641	0.641	0.628	0.003429
ZJS	0.639	0.638	0.636	0.639	0.642	0.646	0.649	0.652	0.657	0.663	0.668	0.667	0.669	0.651	0.003867
AHS	0.699	0.699	0.698	0.704	0.707	0.717	0.718	0.718	0.721	0.724	0.726	0.722	0.721	0.713	0.002594
FJS	0.677	0.677	0.676	0.680	0.688	0.697	0.695	0.694	0.697	0.700	0.703	0.702	0.700	0.691	0.002828
JXS	0.733	0.732	0.730	0.733	0.741	0.749	0.747	0.748	0.749	0.751	0.753	0.749	0.749	0.743	0.001751

SHD	0.617	0.617	0.616	0.620	0.622	0.625	0.628	0.631	0.636	0.639	0.644	0.643	0.644	0.629	0.003503
HEN	0.654	0.654	0.653	0.658	0.662	0.665	0.668	0.670	0.675	0.679	0.683	0.681	0.681	0.668	0.003463
HUB	0.682	0.682	0.681	0.687	0.692	0.699	0.700	0.702	0.705	0.707	0.710	0.706	0.705	0.697	0.002821
HUN	0.682	0.682	0.681	0.687	0.691	0.699	0.701	0.702	0.706	0.708	0.710	0.707	0.707	0.697	0.003008
GDS	0.601	0.600	0.599	0.602	0.605	0.608	0.612	0.615	0.620	0.625	0.630	0.629	0.631	0.614	0.004172
GXZ	0.730	0.729	0.727	0.734	0.742	0.749	0.746	0.745	0.746	0.748	0.750	0.747	0.746	0.742	0.001844
HAN	1.000	0.899	0.931	0.972	0.939	1.000	1.000	1.000	1.000	0.959	0.947	1.000	1.000	0.973	0.001017
CQS	0.755	0.754	0.752	0.760	0.768	0.775	0.772	0.771	0.769	0.770	0.769	0.762	0.759	0.764	0.000464
SCS	0.674	0.673	0.672	0.677	0.681	0.690	0.690	0.690	0.695	0.697	0.699	0.695	0.694	0.687	0.002473
GZS	0.804	0.802	0.800	0.805	0.809	0.819	0.818	0.817	0.822	0.825	0.827	0.820	0.816	0.814	0.001288
YNS	0.733	0.734	0.733	0.739	0.746	0.758	0.757	0.757	0.762	0.765	0.768	0.763	0.761	0.752	0.003126
SNX	0.744	0.742	0.739	0.743	0.748	0.757	0.755	0.754	0.755	0.756	0.758	0.753	0.751	0.750	0.000861
GSS	0.801	0.798	0.796	0.800	0.809	0.818	0.815	0.816	0.818	0.822	0.826	0.821	0.817	0.812	0.001711
QHS	1.000	0.994	0.996	1.000	0.998	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	0.999	0.000003
NXZ	0.980	0.974	0.967	0.970	0.980	0.986	0.981	0.979	0.975	0.972	0.972	0.964	0.958	0.974	-0.001863
XJZ	0.772	0.771	0.771	0.775	0.783	0.793	0.791	0.791	0.795	0.801	0.806	0.801	0.799	0.788	0.002865

Table 5: Results of the Wilcoxon-Mann-Whitney Rank-Sum test

Index	Null Hypothesis (Ho)	p-value
Overall efficiency	Mean(unregulated)= Mean(regulated)	0.07
Production efficiency	Mean(unregulated)= Mean(regulated)	0.01
Eco-efficiency	Mean(unregulated)= Mean(regulated)	0.06

Figure 1: Sustainability efficiency index

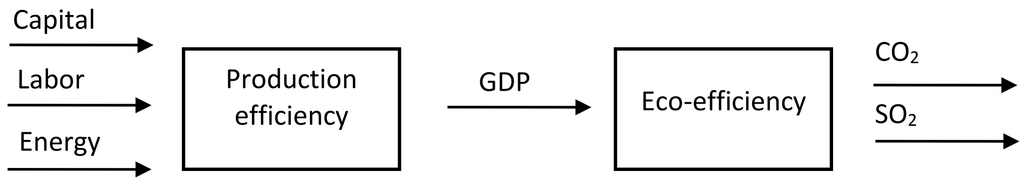


Figure 2: Map of Chinese provinces with overall sustainability efficiency scores

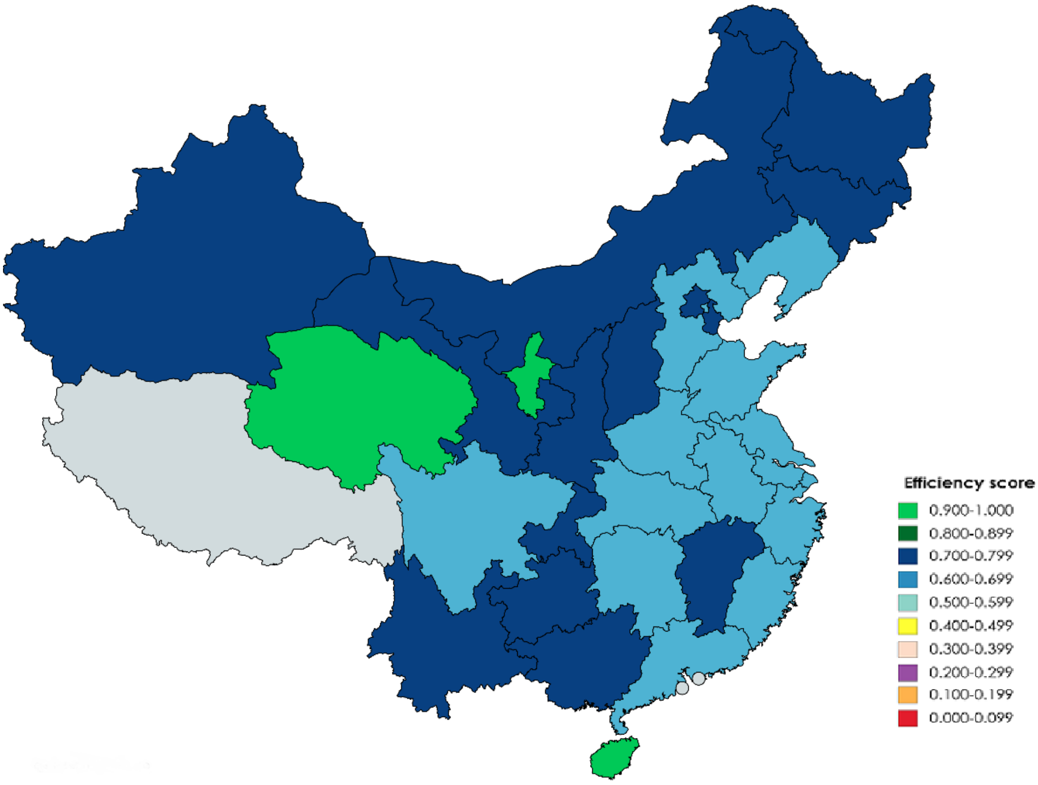
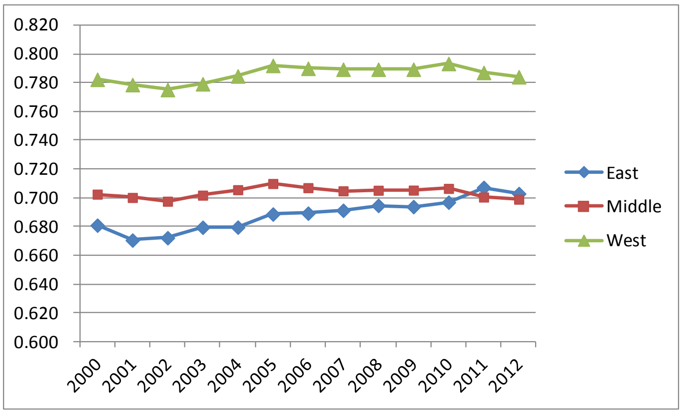
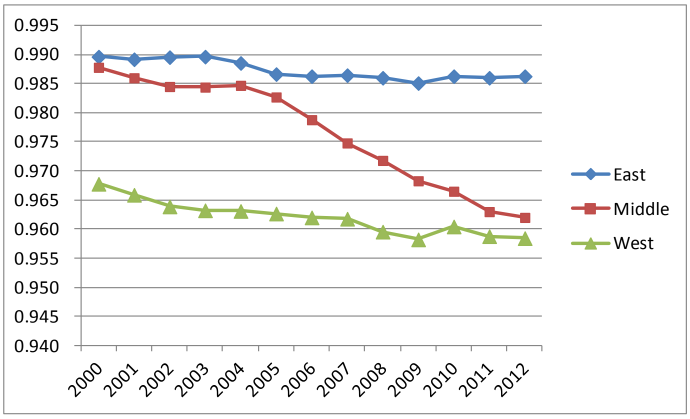


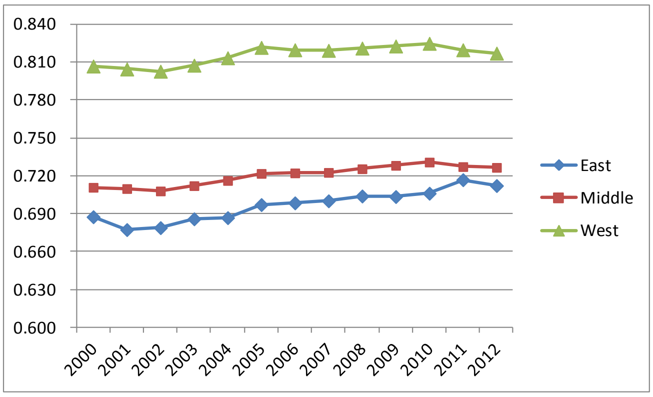
Figure 3: The sustainability efficiency dynamics of different areas.



a. the overall efficiency

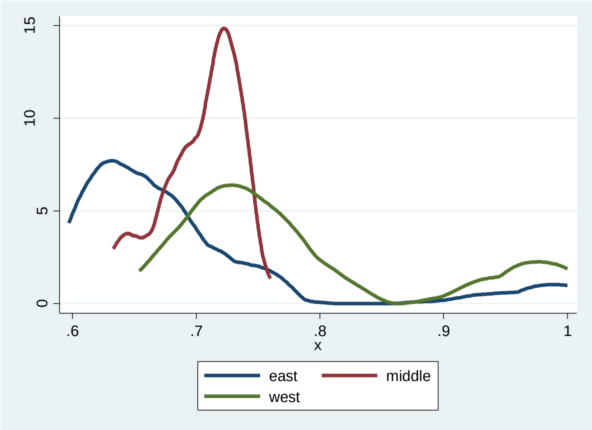


b. the production efficiency

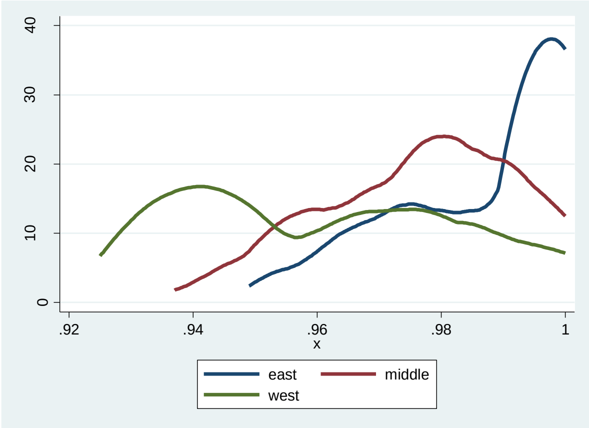


c. the eco-efficiency

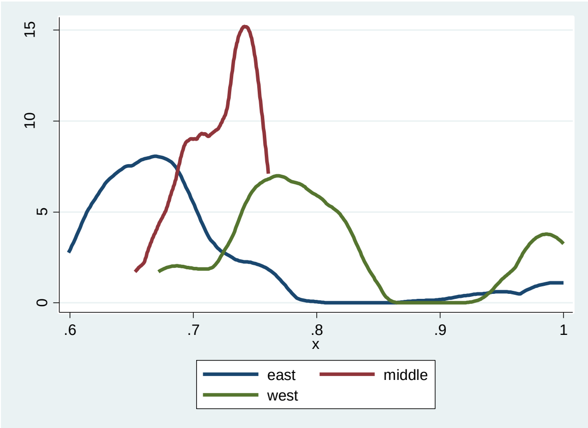
Figure 4: the distribution of different areas.



a. overall efficiency

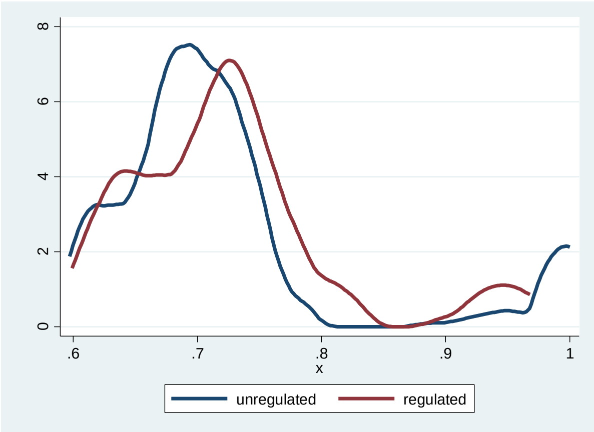


b. production efficiency

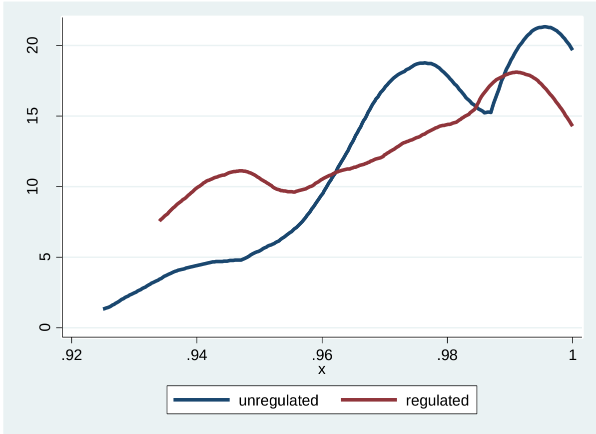


c. eco-efficiency

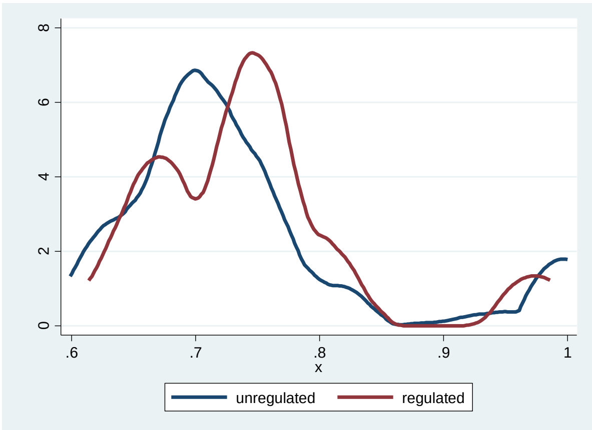
Figure 5: the distribution of unregulated and regulated area



a. Overall efficiency



b. Production efficiency



c. Eco-efficiency

Figure 6: the box plots of unregulated and regulated area

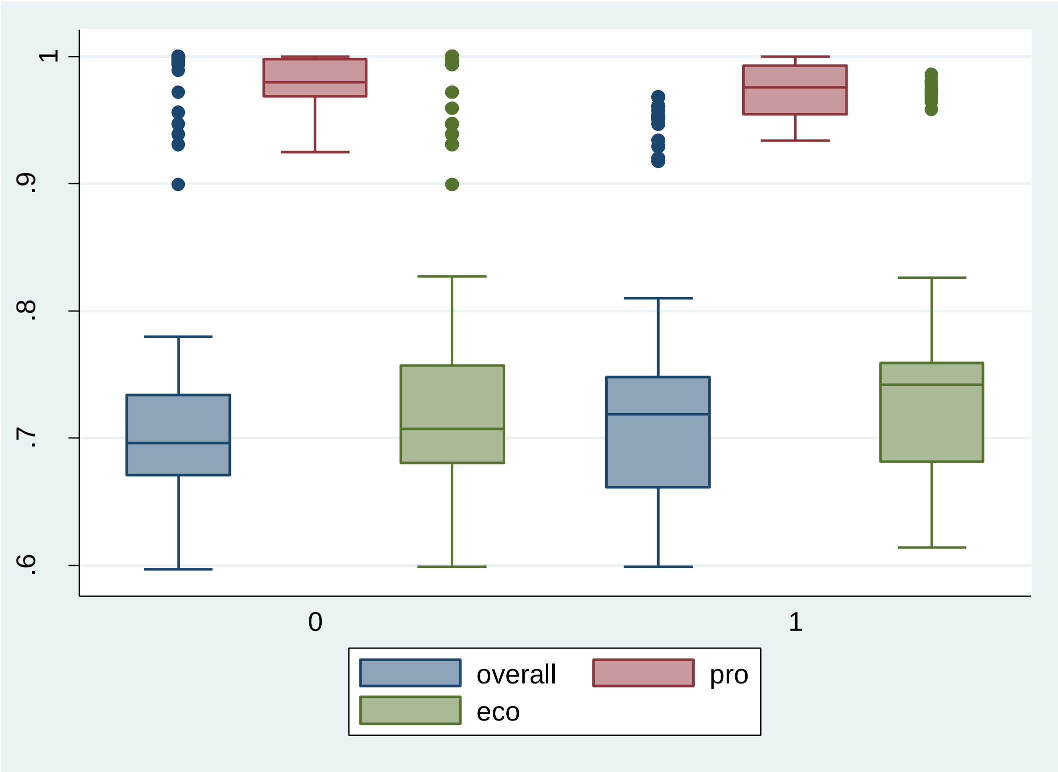
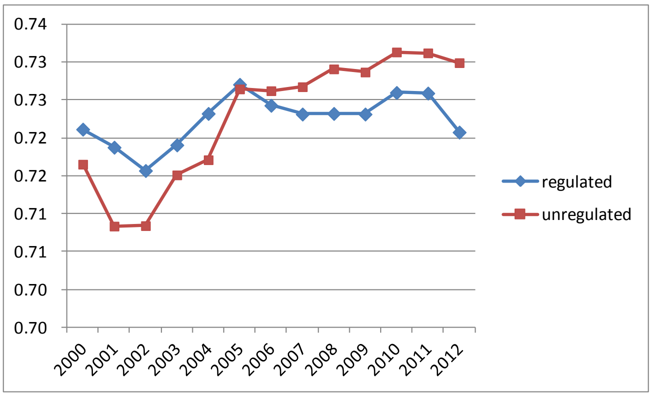
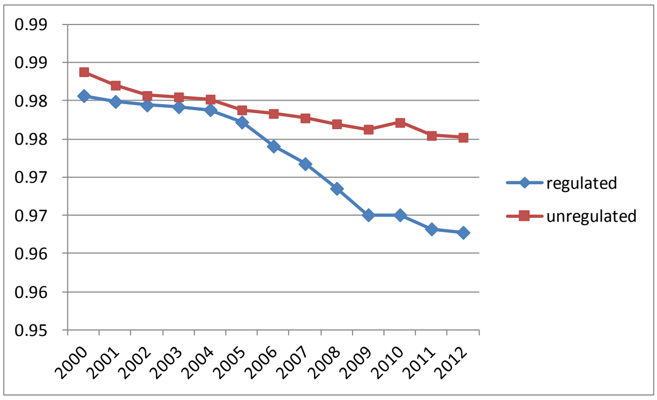


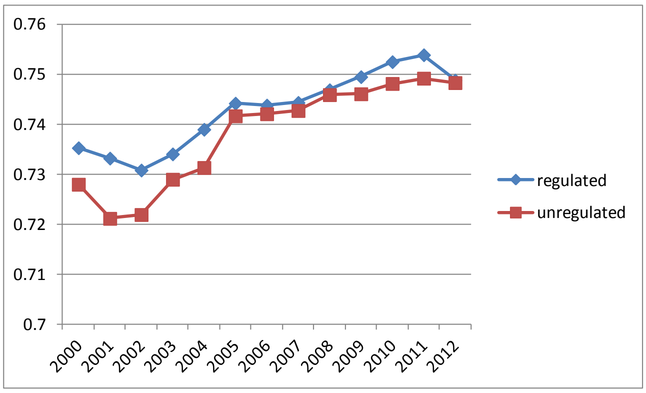
Figure 7: The sustainability efficiency dynamics of regulated and unregulated area.



a. overall efficiency



b. production efficiency



c. eco-efficiency